AN ADAPTIVE HYBRID IMAGE COMPRESSION METHOD AND ITS APPLICATION TO MEDICAL IMAGES

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ABSTRACT

An efficient adaptive lossy image compression technique using classified vector quantiser and singular value decomposition for compression of medical magnetic resonance – brain images is presented. The proposed method is called adaptive hybrid classified vector quantisation. A simple but efficient classifier based gradient method without employing any threshold to determine the class of the input image block in the spatial domain that results in a high-fidelity medical compressed image was utilised. The proposed technique was benchmarked with JPEG-2000 standard. Simulation results indicated that the proposed approach can reconstruct high visual quality images with higher Peak Signal-to Noise-Ratio than the benchmarked technique, and also meet the legal requirement of medical image archiving.

Index Terms— magnetic resonance image, Classified vector quantiser, image compression, singular value decomposition.

1. INTRODUCTION

Image compression plays an important role in the transmission and storage of image information as a result of bandwidth and storage limitations. The goal of image compression is to obtain a representation that minimises bit rate with respect to some distortion constraint.

Medical image compression plays a key role as hospitals move towards filmless imaging and go completely into computerized imaging. The use of medical images for diagnosis purposes has become necessity. But the storage demands of such images are very high. This has provoked significant interest in the field of medical image compression. Image compression will allow Picture Archiving and Communication Systems (PACSs) to reduce the file sizes on their storage requirements while maintaining relevant diagnostic information. Teleradiology sites benefit since reduced image file sizes yield reduced transmission times.

Image compression techniques can be classified into two categories: Lossless compression and Lossy compression. In Lossless compression, the reconstructed image is identical to the original one and results in low compression ratio, the compression ratio could be as low as 2:1 to 3:1. On the other hand, Lossy compression methods allow a loss in the actual image data, so the original image cannot be created exactly from the compressed image. Its main advantage is higher compression ratio, it can provide compression ratios more than 10:1 with little perceptible difference between reconstructed and original images; however, lossy compression introduces some error in the data because of the loss in the actual image data. The motivation for lossy compression originates from the inability of lossless algorithms to produce as low bit rates as desired.

It is expected that the volume of uncompressed data produced by hospitals will exceed capacity and drive up costs even as the capacity of storage media continues to increase. However, unlike many other compression applications, medical imaging application demands lossless or high-fidelity image compression. It is clear that lossless compression is a legal technical approach by ensuring perfect reconstruction of the original. But after decades of active research on lossless compression, the achievable compression ratio remains low. Recent studies have shown that, compression ratios of 3: 1 or 4: 1 with more complex lossless compression, are possible [1]. Lossless compression alone is in general insufficient to attain ratios better than 4:1. It is then natural to turn to schemes for lossy compression that have provided excellent results for nonmedical images.

Recently, several independent research groups [2-4] working with different lossy compression algorithms have found that lossy compressed medical images with high fidelity don't affect the diagnostic accuracy in a statistically significant way. Lossy techniques with compression ratios of about 10:1 are commonly adopted for PACSs for use in primary diagnosis and clinical review, using DICOMJPEG or JPEG2000 compression algorithms [5]. However, the proposed technique is evaluated at compression ratio slightly higher than 10:1 to demonstrate its efficiency.

Popular transform-based lossy compression techniques such as discrete cosine transform (DCT) or wavelet/subband coding tends to introduce artifacts at high frequency signal components. Their coding efficiency is influenced when image compression of very high fidelity is required since such details often represent high frequency components in frequency domain. Unlike transform-based image coding methods that compress images in frequency domain, VQ [6] is very efficient approach to low bit rate image compression that compresses images directly in spatial domain. It is easier to achieve very high fidelity everywhere in the reconstructed image with a spatial domain compression method than with a transform domain method. For instance, with a fixed VQ codebook one knows the possible maximum distortion at any pixel independent to input images, whereas no nontrivial bound can be placed on

maximum distortion at a pixel with transform-based methods. However, a serious problem in VQ is edge degradation caused by employing a distortion measure such as the mean square error (*MSE*) for searching the closest codeword in the codebook. To tackle this problem, the classified VQ (CVQ) was introduced by Ramamurthi and Gersho [7].

Another efficient method for image compression is the singular value decomposition (SVD) [8]. The use of SVD in image compression is motivated by its excellent energy compaction in the least square sense. As a consequence, the use of SVD technique in image compression has been widely studied [9, 10]. SVD generally relies on" global" information derived from all the vectors in the dataset, which is more effective for datasets consisting of homogeneously distributed vectors. For databases with heterogeneously distributed vectors, more efficient representation can be generated by subdividing the vectors into groups, with each of which being characterised by a different set of statistical or/and geometrical parameters. Based on this insight, we recently proposed a new method called improved hybrid classified vector quantisation (IHCVQ) [11] which was an adaptive classified method and resulted in a high visual quality in nonmedical images. In this paper, we will tailor (IHCVQ) to high-fidelity medical image compression.

2. VECTOR QUANTISATION and CLASSIFIED VECTOR QUANTISER

2.1. Vector Quantisation (VQ)

A vector quantiser [6] is defined as a mapping $\mathbf{Q}$ from a k dimensional Euclidean space R^k to a finite subset Y of R^k. That is, $\mathbf{Q}: R^K \rightarrow Y$. This finite set $Y = \{\mathbf{y}_{i:}\ i = 1… N\}$, where N is the size of the set Y, is called a VQ codebook, and $\mathbf{y}_i$ represents the ith codeword (codevector) in the codebook Y. In VQ scheme, the image is divided into small nonoverlapping blocks. For example 4×4 pixel block is considered as vector of dimension 16. VQ maps input vectors into a set of codevectors. Similar vectors are mapped to the same codevectors in the codebook.

The operations of VQ can be divided into three major steps: a codebook generation, an encoder that assigns each input vector $\boldsymbol{x} \in R^k$ to an index i, and a decoder that finds the codevector by the transmitted index i. The codebook is generated from a set of training vectors. The most commonly used algorithm to obtain a codebook is an iterative clustering algorithm such as k-means, or a generalised Lloyd clustering algorithm (LBG) [12].

2.2. Classified Vector Quantiser (CVQ)

A CVQ [7] coder based on a composite source model is a proposed solution of edge degradation problem associated with VQ scheme. It consists of a classifier and separate codebooks for each class. The possible classes are typically: shade, horizontal edge, vertical edge and diagonal edge classes. Each block is classified into one of the appropriate classes using a suitable classifier. Separate subcodebooks

were designed for each of the classes. In CVQ technique, in addition to higher quality edge reproduction, the computational complexity can also be reduced. This relate to the fact that only one appropriate subcodebook has to be searched for the closest codeword to each input vector since the searching process for the closest codeword to the input vector is performed on a specific subcodebook that contains small number of codeword.

3. SINGULAR VALUE DECOMPOSITION (SVD)

SVD is a well-known method in linear algebra [8] to diagonalize a rectangular $m \times n$ matrix A by factorizing it into three matrices U, S, and V, such that,

$$A = USV^T \tag{1}$$

where S is a diagonal $m \times n$ matrix with elements s_i along the diagonal and *zeros* everywhere else. U and V are orthonormal matrices with sizes $m \times m$ and $n \times n$, respectively, and V^T is the transpose of the matrix V. The matrix U is called the left singular matrix, V is called the right singular matrix, and the diagonal matrix S is the singular values matrix. SVD has several applications to multimedia including image compression [9, 10].

4. PROPOSED METHOD

Like any compression system, the proposed technique consists of an encoder and a decoder.

At the encoder, fixed small size 4×4 blocks is utilised to achieve good subjective quality images. At the outset, the block mean value is calculated and subtracted from each pixel in the block. Let $B = \{b_{ij};\ 1 \le i, j \le 4\}$ represents a 4×4 image block. In this case b_{ij} is the gray level pixel value corresponding to position (i, j) of row i and column j in the image block B. The discrete gradients of the block B in the x and in the y directions are determined as follows:

$$G_x = \frac{1}{8} \Big[\sum_{i=1}^{2}\sum_{j=1}^{4} b_{ij} - \sum_{i=3}^{4}\sum_{j=1}^{4} b_{ij} \Big]$$
$$G_y = \frac{1}{8} \Big[\sum_{i=1}^{4}\sum_{j=1}^{2} b_{ij} - \sum_{i=1}^{4}\sum_{j=3}^{4} b_{ij} \Big] \tag{2}$$

The gradient magnitude within each image block are defined by

$$|G| = \sqrt{\left(G_x^2 + G_y^2\right)} \tag{3}$$

Let $\rho(B)$ represents the spectral radius of a block B, which is the modulus of its dominant eigenvalue defined by:

$$\rho(B) = \max\{|\lambda_i|\}, i = 1,2,3,4 \tag{4}$$

where λ_i, $i = 1,2,3,4$ are the eigenvalues of the block B_{4x4}.

If the gradient magnitude |G| in equation (3) of the block B is smaller than $\rho(B)$ in equation (4), the block contains no significant gradient and it is classified as a shade block; otherwise, it is an edge block. Various masks are then used to determine the class of the edge block, based on the edge orientation in the spatial domain. The edge blocks are divided into four classes, namely, horizontal, vertical, diagonal 45º and diagonal 135º determined using the

following four convolution masks [13]; where, V, H, U, and L are vertical, horizontal, upper diagonal, and lower diagonal masks, respectively. As we can see from the four masks, these masks can determine the block shape.

$$V=\begin{bmatrix} -2 & -1 & 1 & 2 \\ -2 & -1 & 1 & 2 \\ -2 & -1 & 1 & 2 \\ -2 & -1 & 1 & 2 \end{bmatrix} \quad H=\begin{bmatrix} 2 & 2 & 2 & 2 \\ 1 & 1 & 1 & 1 \\ -1 & -1 & -1 & -1 \\ -2 & -2 & -2 & -2 \end{bmatrix}$$

$$U=\begin{bmatrix} 5 & 2 & 1 & 0 \\ 2 & 1 & 0 & -1 \\ 1 & 0 & -1 & -2 \\ 0 & -1 & -2 & -5 \end{bmatrix} \quad L=\begin{bmatrix} 0 & 1 & 2 & 5 \\ -1 & 0 & 1 & 2 \\ -2 & -1 & 0 & 1 \\ -5 & -2 & -1 & 0 \end{bmatrix}$$

The absolute values of the four convolution results are defined as Value1, Value2, Value3, and Value4. These four values are used to determine the block class as follows:

1) Vertical class: The block belongs to this class if Value1 > Value2 and | Value1 − Value2 | > | Value3 − Value4 |.

2) Horizontal class: The block belongs to this class if Value1< Value2 and | Value1 − Value2 | > | Value3 − Value4 |.

3) Diagonal class (45°): The block belongs to this class if Value3 > Value4 and | Value3 − Value4 | > | Value1 − Value2 |.

4) Diagonal class (135°): The block belongs to this class if Value3 < Value4 and | Value3 − Value4 | > | Value1 − Value2|.

Once the block classification process has been completed, five different subcodebooks are generated, representing the different orientations of edge block information and the shade block using SVD-based VQ. Different rank values have been used in the codebook generating process according to the type of the codebook. Figure 1 shows the block diagram of the proposed AHCVQ encoder.

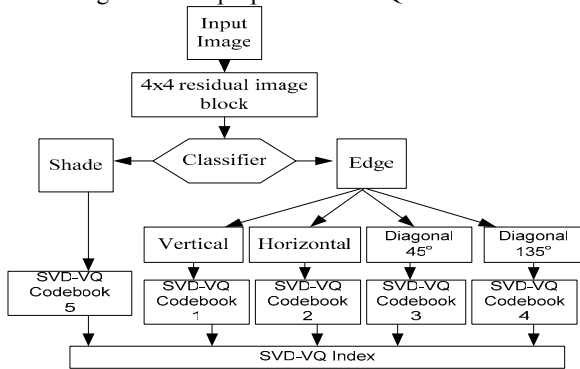
Figure 1. The block diagram of the proposed AHCVQ encoder

At the decoder, a simple look-up table operation is performed to retrieve the corresponding codeword from the same codebook as the encoder used, and computes the inverse SVD transform. As the residual block is used in the encoding process, the block mean value is added to the reconstructed image block

5. SIMULATION RESULTS

Simulations were carried out to test the performance of the new proposed approach on medical images. The codebook is constructed using SVD trained by a collected image, which contains parts of different organs, include MR brain, heart, and lungs images to be an 512×512 image, as in Figure 2.

Table 1 shows the performance of the proposed AHCVQ method, while Figure 3 shows some of the reconstructed compressed images. The original images are gray scale images with 8 bits per pixel. Matlab code is written for the generation of the proposed AHCVQ.

The performance of this scheme is usually characterised using the mean square error (*MSE*), and the Peak Signal to Noise Ratio (*PSNR*). Both the *MSE* and *PSNR* are defined, respectively, as follows:

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(x_{ij} - y_{ij} \right)^2 \qquad (5)$$

where *MN* is the total number of pixels in the block.

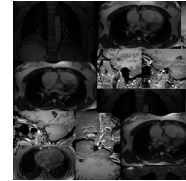$$PSNR = 10 \log_{10} \left(\frac{255^2}{MSE} \right) \qquad (6)$$

Figure 2. A collected image used as a training set

Table 1. Reconstruction performance for AHCVQ trained on the collected image. This test is calculated by using approximately the same bit-rate.

| Image | AHCVQ | | JPEG-2000 | |
	Bitrate (bpp)	PSNR (dB)	Bitrate (bpp)	PSNR (dB)
im_111	0.7369	35.9219	0.7510	35.1770
im_117	0.7473	35.3683	0.7568	34.6183
im_101	0.7874	34.5276	0.7756	33.5979
im_031	0.4083	39.5061	0.4060	38.9104

The results in Table 1 show that, in all cases, the proposed AHCVQ using SVD-based VQ outperformed JPEG-2000 which was generated using Matlab as shown in [14] in terms of the *PSNR* as the image quality measure.
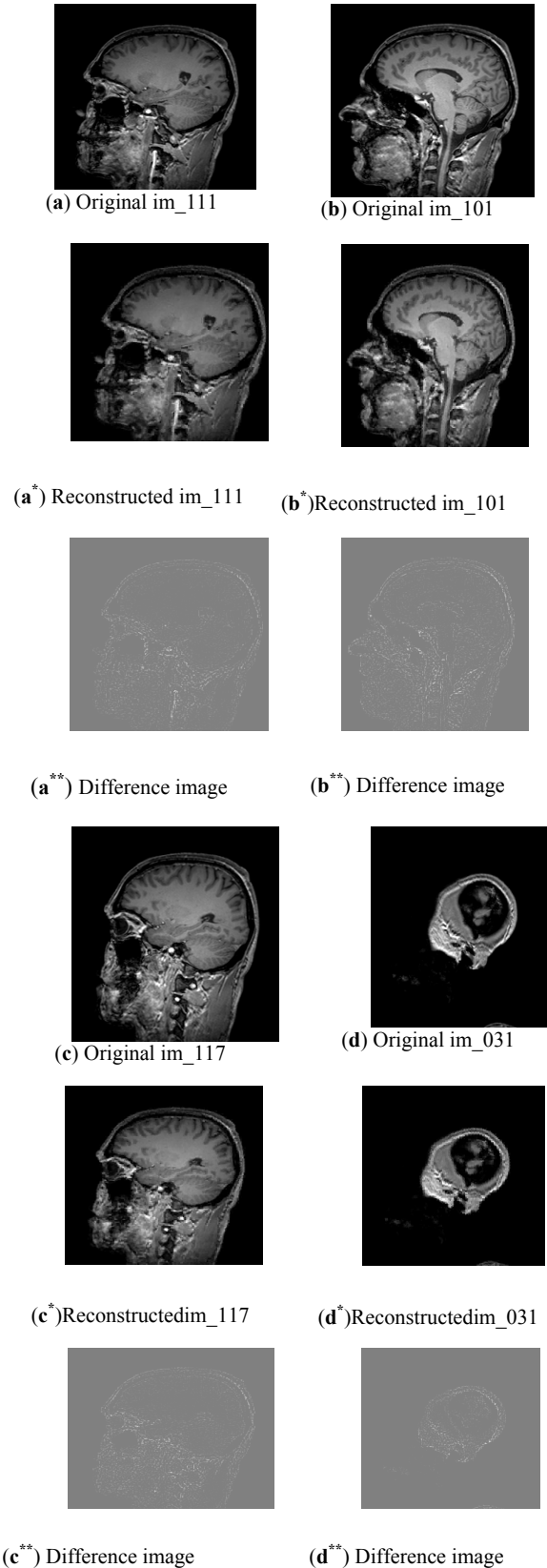
(**a**) Original im_111

(**b**) Original im_101

(**a**[*]) Reconstructed im_111

(**a***) Reconstructed im_111

(**b***)Reconstructed im_101

(**a****) Difference image

(**b****) Difference image

(**c**) Original im_117

(**d**) Original im_031

(**c***)Reconstructedim_117

(**d***)Reconstructedim_031

(**c****) Difference image

(**d****) Difference image

Figure 3. Original MRI brain images, their constructed images, and difference image of each test image in the dataset of Table 1.

6. CONCLUSION

A novel medical image compression technique in the spatial domain that results in high-fidelity reconstructed image is proposed. Further improvement can be achieved by encoding the difference image using an appropriate method.

REFERENCES

[1] S. M. Perlmutter, *et al*., "Medical Image Compression and Vector Quantization," *Statistical Science*, 13(1), pp. 30-53, 1998.

[2] K. K. Chan, S. Lou, and H. K. Huang, "Full-frame Transform Compression of CT and MR Images," *Radiology,* 171, pp. 847-851, 1989.

[3] P. C. Cosman, *et al.,* "Tree-structured Vector Quantization of CT Chest Scans: Image Quality and Diagnostic Accuracy," *IEEE Trans. Med. Imag.,* 12, pp. 727-739. Dec. 1993.

[4] P. C. Cosman, *et al.,* "Thoracic CT Images: Effect of Lossy Image Compression on Diagnostic Accuracy," *Radiology,* 190, pp. 517-524, Feb. 1994.

[5] D. A. Koff, MD; H. Shulman, MD, FRCPC, FACR, "An Overview of Digital Compression of Medical Images: Can We Use Lossy Image Compression in Radiology?" *CARJ* Vol 57, No 4, pp. 211-217, October 2006.

[6] Gersho, A. and R. M. Gray, Vector Quantization and Signal Compression, Kluwer, Boston, 1992.

[7] B. Ramamurthi and A. Gersho, "Classified Vector Quantization of Images," *IEEE Trans. Commun*. COM-34, pp. 1105-1115, 1986.

[8] Gilbert, S., Introduction to Linear Algebra, Wellesley-Cambridge Press, 1998.

[9] A. Dapena and S. Ahalt, "A Hybrid DCT-SVD Image-Coding Algorithm," *IEEE Trans. Circuits Syst. Video Technol*., 12(2), pp. 114-121, February. 2002.

[10] M. Tian, Si-Wei Luo, Ling-Zhi Liao, "An Investigation into Using Singular Value Decomposition as a Method of Image compression," *Machine Learning and Cybernetics*, 2005, Proceedings of 2005 International Conference, vol. 8, pp. 5200-5204, 18-21 Aug.2005.

[11] A. J. Hussain, A. Al-Fayadh, D. Al-Jumeily, P. Lisboa and P. Liatsis, "Image Compression Using Improved Hybrid Classified Vector Quantisation," *ELECTRONICS LETTERS*, Vol. 43, No. 7, pp. 385-387, March 2007.

[12] Y. Linde, A. Buzo, and R. M. Gray, "An Algorithm for Vector Quantizer Design," *IEEE Trans. Commun*., vol. COM-28, pp. 84-95, January 1980.

[13] C. H. LEE, and L.H. CHEN, " Novel Image Compression Method Using Edge-Oriented Classifier and Novel Noiseless Coding Method," *IEE Proc.-Vis. Image Signal Process.*, vol. 144., no. 6, Dec.1997.

[14] Gonzalez, R. C., R. E. Woods, and S. L. Eddins, Digital Image Processing Using Matlab, 2004.